# CALIBRATION-BASED METHODS FOR CORRECTING COARSE RESOLUTION ESTIMATES OF LAND-COVER PROPORTIONS

A. Moody* and C. E. Woodcock†

*Department of Geography, University of North Carolina at Chapel Hill, 203 Saunders Hall, Chapel Hill, NC, 27599-3220, USA.

†Department of Geography, Center for Remote Sensing, Boston University, 725 Commonwealth Ave., Boston, MA, 02215, USA.

## ABSTRACT

Calibration-based models for correcting estimates of land-cover proportions at a series of scales produce varied results. A model based only on the scale-dependent errors observed at the calibration site performs poorly because it reflects only the error specific to the calibration site and therefore lacks generalizability. A model based on the coefficients of scale transition lines successfully corrects error for large and small classes but does not perform as well for classes of intermediate original size. Finally, a model based on matrices of scale-specific interclass transitions or confusions produces the best results. This success probably occurs because the transition matrices carry some information about the spatial characteristics of the landscape. The slope based model will probably generalize most successfully and would likely perform better with the explicit incorporation of measures of landscape spatial pattern.

## INTRODUCTION

Effective modeling of Earth system processes depends on the accurate knowledge of the nature, extent and location of land-surface cover at local to global scales. Models of biomass productivity and functioning, surface energy balance, hydrologic processes, chemical cycling and climate all incorporate some representation of land cover to drive certain model components. Similarly, monitoring and management of Earth resources require reliable information about the nature and extent of natural and human-induced land-cover transformations. The scales at which land-cover data are needed, and the extent of regions undergoing transformation suggest that monitoring land cover and land-cover change is most effectively accomplished through synoptic, relatively small-scale mapping missions employing remotely sensed data.

The best current option for determining global land cover and land-cover change involves the use of coarse spatial resolution, high temporal frequency data such as that produced by the NOAA/AVHRR sensors. However, the accuracy with which land cover and land-cover changes can be represented is directly linked to the sampling scale. In the remote sensing situation, both the locational accuracy as well as the proportional, or areal accuracy are influenced by increased pixel size. The scale-dependence of accuracy is related not only to the spatial resolution of the sensor, but to the interaction between the sensor resolution and the spatial characteristics of the phenomenon being mapped. For monitoring rates of processes such as tropical deforestation, areal accuracy is particularly critical.

Likewise, if land-cover data are to be used as input to models of Earth syste processes, the areal and thematic accuracy of those data are important relative locational accuracy. If accurate mapping of land cover and land-cover change to be successful over large regions, it is necessary to improve techniques f extracting land-cover information from coarse-scale remotely sensed data, or develop methods for the *a posteriori* correction of land-cover area estimates.

In this research, we evaluate several methods for improving coarse-resolutic estimates of land-cover proportions using calibration based correction procedure Scaling models developed for a calibration location are inversely applied to a te location and the models are evaluated with respect to their ability to impro coarse-scale estimates of land-cover proportions for the test site. The calibratic and testing sites are the Plumas National Forest and the Stanislaus National Fores respectively. Both are located in the Sierra Nevada Mountains in California ar are composed of the same basic cover types.

## BACKGROUND

Efforts to map continental or global scale land cover using remotely sens data have typically used time-series data from the NOAA-AVHRR (Advanc Very High Resolution Radiometer) series of satellites at either 1.1 km or rough 18 sq. km. resolution. Vegetation classification is based on time-series of ma imum value composited NDVI (Normalized Difference Vegetation Index) data either a) unsupervised clustering based on the temporal signatures (Townshend al. 1987); b) clustering based on variables that are derived from the temporal si natures (Lloyd 1990); c) supervised classification in temporal space (Lambin, press); d) decision tree classification based on predetermined critical thresholds NDVI and surface temperature values (Running et al. 1994; Lambin and Ehrlic in press).

A variety of factors can lead to error in the results of classifications pe formed in this way. One source of error is the interaction between the spatial pa terns or the scales of variability in the landscape and the spatial resolution which the landscape is being measured and represented (Woodcock and Strahl 1987; Townshend and Justice 1988). Consequently, the retrieval of area estimat from coarse spatial resolution land-cover maps may be problematic. Th difficulty in part is due to the effect of spatial aggregation on land-cover propo tions. Classes which dominate the original landscape will tend to be increasing over-represented as coarser resolutions are used to sample the landscape. Co versely, small classes will be overwhelmed by the signal for the more domina classes, and will tend to disappear as the landscape is sampled at coarser scal (Turner et al. 1989; Moody and Woodcock 1994; Moody and Woodcock, press). This general effect is modulated by other elements of landscape patte specifically the level of aggregation of the classes and the adjacencies of differe classes in the landscape (Turner et al. 1989; Moody and Woodcock 1994; Mooc and Woodcock, in press). This scenario discounts the influence of problems ass ciated with spectral mixing, atmospheric effects and sensor response characteri tics.

Under the assumption that scale dependent error results solely from the sp tial effects outlined above, it should be possible to model analytically the loss information with coarser resolution given enough information about the spati properties of the landscape (Turner et al. 1989). An alternative approach correcting proportional error in coarse resolution land-cover datasets is to develc

# 1995

# ACSM/ASPRS

## Annual Convention & Exposition Technical Papers

ACSM 55th Annual Convention
ASPRS 61st Annual Convention

Volume Three: ASPRS

Charlotte, North Carolina
February 27 - March 2, 1995

empirical scaling relationships for small representative areas for which accurate high resolution land-cover data are available. These scaling models can then be inversely applied to other locations of the same general type for which only coarse-scale data is available. Mayaux and Lambin (in press) have experimented with a related approach based on a linear model of a proportion-scaling relationship between 30-m and 1 km data adjusted by a spatial pattern descriptor. In this paper we test the performance of three distinctive calibration based methods at a series of resolutions for a local scale test site.

## METHODS

The calibration site is the Plumas National Forest in the Northern Sierra Nevada Mountains in California. This is a 7320 sq. km. mountainous area with high relief. The vegetation is composed of shrub formations and pine and oak woodlands at the lower elevations, mixed conifer and riparian hardwoods at intermediate elevations, and mixed conifer combined with brush at higher elevations. Brush and grasslands are distributed throughout the area and small rock outcrops exist at high elevations. The test location is the Stanislaus National Forest. This area is also located in the Sierra Nevadas roughly 1.5° south of the Plumas site and its vegetation can be characterized in much the same way. Both sites have been studied as part of a project to develop vegetation mapping and timber inventory procedures for the U. S. Forest Service (Woodcock et al. 1993). Land-cover maps have been produced using Landsat Thematic Mapper imagery and unsupervised image classification supported by air-photo and field validation. cover classes include *grass/barren*, *brush*, *hardwood*, *conifer* and *water*.

For both sites, the 30-m land-cover data was aggregated to a series of coarser scales using a plurality-based aggregation procedure. For each coarser resolution of interest, a grid is coded with the value of the most frequently occurring cover class within each grid cell. Using this method, new maps were generated at 150, 240, 510 and 1020 meter resolution. Using the Plumas data, the relationship between the 30-m land-cover proportions and the proportions at each coarser scale were determined using three different methods. Each of these methods was then applied to the coarse-scale estimates of cover-type proportions for the Stanislaus and evaluated with respect to their ability to correct back to estimates of the actual proportions as determined at 30-m.

The first method is termed Proportion Correction defined as:

$$E_{ir} = \frac{P_{ir} - P_{io}}{P_{io}} \tag{1}$$

where $E_{ir}$ is the proportion estimation error for class $i$ at resolution $r$, $P_{ir}$ is the measured proportion at resolution $r$, and $P_{io}$ is the actual proportion of class $i$. This measure of error is normalized to be relative to the original size of each individual class, rather than relative to the entire scene. The equation for $E_{ir}$ can be inverted to solve for $P_{io}$ if a calibration based estimate of $E_{ir}$ exists. This relationship takes the form of:

$$\hat{P}_{io_t} = \frac{P_{ir_t}}{E_{ir_c} + 1} \tag{2}$$

where $\hat{P}_{io_t}$ is the estimated value of the true proportion for the test site $t$, and $E_{ir_c}$ is the measured estimation error for the calibration site $c$. The calibration estimation errors ($E_{ir_c}$) for the Plumas Forest are presented in Table 1.

*Table 1*. Plumas National Forest estimation errors ($E_{ir}$ from Eq. 1) used for the Proportion Correction (PC) of the coarse resolution Stanislaus Forest proportion errors.

| Estimation Errors | | | | |
|---|---|---|---|---|
| Class Types | Resolution | | | |
| | 150 m | 240 m | 510 m | 1020 m |
| barren | -34.60 | -45.58 | -60.91 | -71.46 |
| brush | -8.79 | -16.96 | -30.83 | -45.08 |
| hardwood | -8.04 | -10.02 | -12.67 | -14.96 |
| water | 64.28 | 10.56 | 11.69 | 6.37 |
| conifer | 11.68 | 17.03 | 26.24 | 34.26 |

The second method is the Transition Correction defined as:

$$\vec{P}_{o_t} = \mathbf{T}_{r_c} * \vec{P}_{r_t} \tag{3}$$

where $\mathbf{T}_{r_c}$ is a class transition, or confusion matrix developed from the calibration site, $\vec{P}_{r_t}$ are the measured class proportions from the test site at resolution $r$, and $\vec{P}_{o_t}$ are the estimates of true class proportions for site $t$. The elements of matrix $\mathbf{T}_{r_c}$ represent the percentage of each class which is classified at each of the *other* classes at resolution $r$. The transition matrix ($\mathbf{T}_{r_c}$) of the aggregated cover types at 1020 m resolution for the Plumas Forest is presented in Table 2. Following this table, 64 percent of the 30 m pixels that are classified as *barren* after aggregation to 1020 m are actually called *barren* at the original resolution. Roughly 20% of those pixels were actually *brush* at the original resolution. Similar calibrations matrices were generated for each aggregation level for the Plumas Forest.

The third method is the Slope Correction and is based on a regression relationship between the correct and estimated cover-type proportions for the calibration site as follows:

$$\hat{P}_{io_t} = \frac{P_{ir_t} - \beta_{r_c}}{m_{r_c}} \tag{4}$$

where $\beta_{r_c}$ and $m_{r_c}$ are the intercept and slope of the proportion transition line developed from the calibration site at resolution $r$. Figure 2 shows the slopes of regression lines relating initial proportions to proportions at coarser resolutions. Each line is based on twenty values; five cover types for four subregions. The slopes and intercepts from these lines are used to supply the values for $\beta_{r_c}$ and $m_{r_c}$ in Equation 4 for calculating the slope corrected values for the Stanislaus.

The success of each method was determined for each of the coarser resolutions (150, 240, 510 and 1020 meters) using a measure of normalized Total Error ($TE_{norm_r}$) defined as follows:

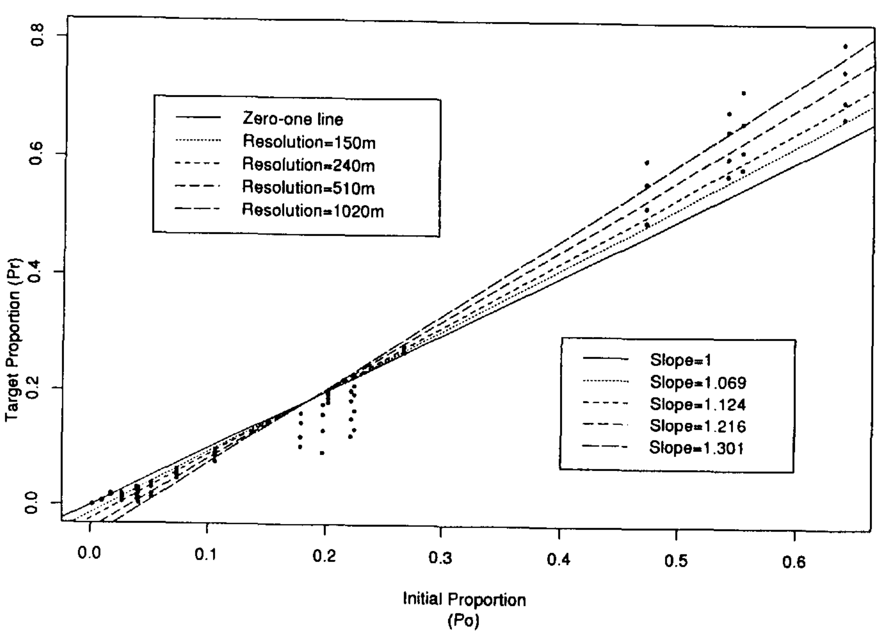
$$TE_{norm_r} = \sum_{i=1}^{n} \left| \frac{\hat{P}_{io_t} - P_{io_t}}{P_{io_t}} \right| \tag{5}$$

where $P_{io_t}$ is the actual proportion of class type $i$ for the test site $t$. This measure normalizes the error based on the original size of the individual classes and treats all classes as equally important.

*Table 2.* Transition matrix representing pixel reassignment due to aggregation from 30 m to 1020 m resolution for the Plumas (calibration) site. This matrix is used in the transition correction (TC) of the 1020 m Stanislaus Forest proportion estimates. The transition between class types and unclassified pixels, and vice versa, are not considered.

| Composition of Land-Cover Classes at 1020 Meters | | | | | |
|---|---|---|---|---|---|
| Components | Aggregated Cover Type | | | | |
| | barren | brush | hardwood | water | conifer |
| barren | 0.644 | 0.118 | 0.040 | 0.068 | 0.039 |
| brush | 0.196 | 0.491 | 0.154 | 0.060 | 0.174 |
| hardwood | 0.053 | 0.122 | 0.520 | 0.047 | 0.127 |
| water | 0.007 | 0.003 | 0.004 | 0.645 | 0.003 |
| conifer | 0.092 | 0.245 | 0.277 | 0.179 | 0.643 |

Figure 2: Plumas Transition Lines






## RESULTS and DISCUSSION

Figure 1 shows the changes in proportions of the five cover types for the Stanislaus Forest as the original 30m land-cover map was aggregated to the series of coarser scales. For each cover type, the distance between its associated line and the line below it represents the proportion of that cover type in the scene at the resolution of interest. Note, in particular, small reductions in the proportions of *barren* and *hardwood*, a moderate reduction for *brush*, and a large increase for *conifer*. Proportions for each resolution were calculated simply as $P_{io} - P_{ir}$ The three correction methods described above were used to correct the coarser resolution proportions back to estimates of the original proportions at 30 m. As described, each correction method was calibrated based on data from the Plumas Forest.

Proportional error $(P_{ir_t} - P_{io_t})$ based on the 1020 m Stanislaus proportion estimates are shown in Figure 3 for the uncorrected data and for the results of all three correction methods. The symbols corresponding to the individual cover types are displayed along the zero-line with respect to their original proportions. Total error values are given for each method.

The Proportion Correction method performs well for *water*, *hardwood* and *conifer*, but quite poorly for the *barren* and *brush* classes. This is the least generalizable method as it presumes that the test site behaves exactly as the calibration site on an individual class basis. This method does not account either for the original proportions of the cover types in the test site, nor for the ways that different cover types interact spatially when scaling is performed.

The Transition Correction and Slope Correction methods both lead to considerable improvements over the uncorrected estimates based on their total error

Figure 1: Stanislaus

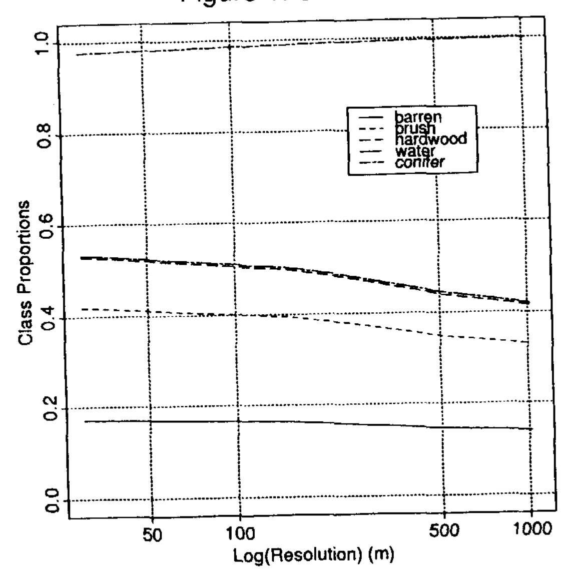
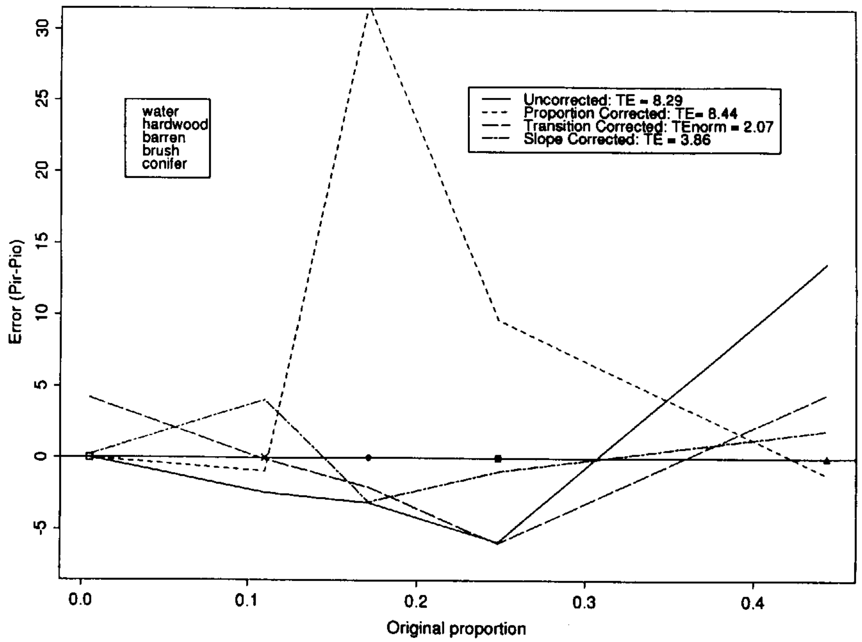


Figure 3: Proportional Error After Correction (1020m) -Stanislaus




values (2.07 and 3.86, respectively). The Transition Correction performs better than the Slope Correction for *hardwood* and *barren*, while the Slope Correction performs better for *conifer* and *water*. Both methods over-correct for *conifer* and under-correct for *barren* and *brush*. The Slope Correction over-corrects for *hardwood* and the Transition Correction over-corrects for *water*.

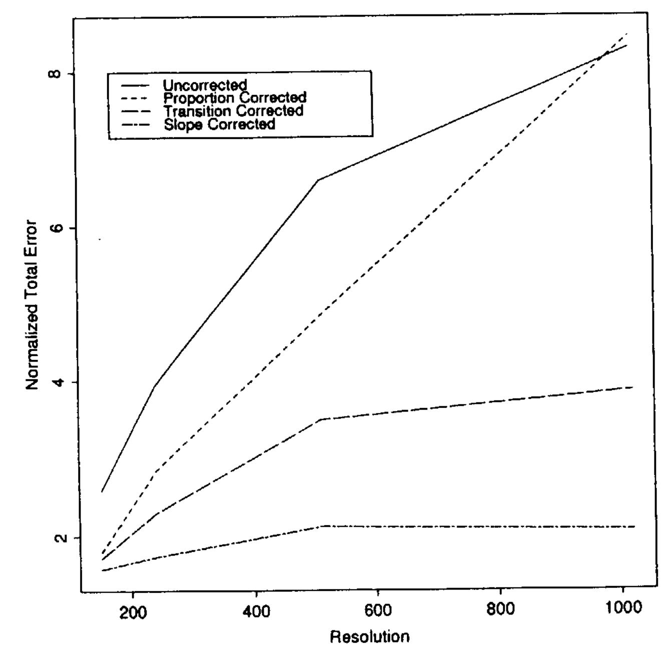
It is probable that the Transition Correction method performs well because the transition matrices carry information that is related to the relative size, spatial pattern and typical adjacencies of the classes in the landscape. Cover types which are spatially dispersed or disaggregated, such as *brush*, will tend to have a low value along the diagonal (correct classification) and will be redistributed among other classes which are more highly aggregated spatially. This effect will in part be modified by the original size of the class under consideration (Turner et al. 1989; Moody and Woodcock 1994). Similarly, there will be a high degree of transition between classes that tend to be adjacent to one another in the landscape. For example, *brush* and *conifer* tend to be spatially associated in the Plumas Forest which is reflected by the relatively high transition values between these two classes in Table 2.

The Slope Correction method probably performs well because it is reflects the generalizable relationship between class proportion and scale. That is, the slope of the lines increase with scale in response to the tendency of small classes to get smaller and large classes to get larger as the scene is aggregated. This general relationship is moderated by spatial effects in the landscape (Turner et al. 1989; Moody and Woodcock in press) and so will result in moderate errors when used to correct proportions across a range of landscape types. In particular, this method will perform poorly for classes of an intermediate size, such as *barren* and *brush* in the Stanislaus dataset, where the general scaling relationship is most unstable.



Figure 4 shows the changes in the total errors ($TE_{norm_r}$) of the different methods as a function of resolution (Eq. 5). Very similar results occur when the non-normalized version of $TE$ is used. The three correction methods all perform fairly well at 150 m resolution. At coarser scales, the Proportion Correction method degrades rapidly until it ultimately produces worse estimates than the original uncorrected data. The Transition Correction method proves to be the most consistent performer, maintaining low $TE_{norm_r}$ values across all resolutions. The Slope Correction method falls between the other two methods, showing a moderate increase in $TE_{norm_r}$ as resolution becomes coarser. These results are consistent with the discussion of Figure 3 above. That is, the Slope Correction method, as a generalizable procedure, will typically perform moderately well and will probably do so over a wide variety of landscapes. However, this method incorporates no information that is specific to the spatial characteristics of the landscape type in question and so will fail to do extremely well, even in two very similar landscapes such as the Plumas and Stanislaus National Forests. The Transition Correction method is more specific to the individual landscape and reflects information about the spatial pattern. While this method does well in the case of the two similar sites presented here, it is probably less extensible than the Slope Correction.

Figure 4: Comparison of Correction Methods -Stanislaus



## CONCLUSIONS

The results suggest considerable potential for the development of calibration-based models for correcting class-specific area estimates from coarse scale datasets. This is significant for global representation of land cover and for monitoring of land-cover change, especially when areal estimates are extracted from such datasets. Models based on the estimation errors derived from the calibration site are too specific to that site and therefore are non-generalizable. Transition Correction is more successful, most likely because it carries some degree of information about the spatial patterns and relationships in the landscape. Slope based models are probably the most generalizable because they reflect relationships that will hold for most landscapes. However they could be improved with the addition of variables that explicitly describe the spatial characteristics of the landscape, such as aggregation, patch size or fractal dimension (Mayaux and Lambin, in press). The incorporation of spatial measures may especially improve the correction of proportions for cover types which are of a moderate size in the landscape. That is, in those cases where the general relationship (large classes grow and small classes shrink with aggregation) does not hold, measures of spatial pattern may help to resolve the scale-dependence of cover-type proportions. Proportion scaling models, such as those presented here, also need to be tested over a broader range of general landscape types to determine their potential extensibility.

## ACKNOWLEDGEMENTS

This work was supported in part by the National Aeronautics and Space Administration under contract NAS5-31369.

## REFERENCES

Lambin, E. F., and Ehrlich, D. Combining vegetation indices and surface temperature for land-cover mapping at broad spatial scales. *Int. J. Remote Sens.* in press.

Lloyd, D. 1990. A phenological classification of terrestrial vegetation cover using shortwave vegetation index imagery. *Int. J. Remote Sens.* 11:2269-2279

Mayaux P., and E. F. Lambin. Estimation of tropical forest area from coarse spatial resolution data: a two step correction function for proportional errors. *Remote Sens. Environ.* in press.

Moody, A. and Woodcock, C. E. 1994. Scale-dependent errors in the estimation of land-cover proportions —Implications for global land-cover datasets. *Photogramm. Eng. Remote Sens.* 60(5): 585-594.

Moody, A. and Woodcock, C. E. The influence of scale and the spatial characteristics of landscapes on land-cover mapping using remote sensing. *Landscape Ecology* in press.

Running, S., Loveland, T. and Pierce, L. 1994. A vegetation classification logic based on remote sensing for use in global biogeochemical models. *Ambio* 23(1)4-8.

Townshend, J. and Justice, C. 1988. Selecting the spatial resolution of satellite sensors required for global monitoring of land transformations. *Int. J. Remote Sens.* 9(2):187-236.

Townshend, J., Justice, C., and Kalb., V. 1987. Characterization and classification



of South American land cover types using satellite data. *Int. J. Remote Sens.* 8(8):1189-1207.

Turner, M., O'Neill, R., Gardner, R. and Milne, B. 1989. Effects of changing spatial scale on the analysis of landscape pattern. *Landscape Ecol.* 3(3/4):153-162.

Woodcock C. E. and Strahler, A. H. 1987. The factor of scale in remote sensing. *Remote Sens. Environ.* 21:311-332.

Woodcock, C. E., Collins, J., Gopal, S., Jakabhazy, V., Li, X., Macomber, S., Ryherd, S., Wu, Y., Harward, V. J., Levitan, J., and Warbington, R. 1993. Mapping forest vegetation using Landsat TM imagery and a canopy reflectance model. submitted to *Remote Sens. Environ.*